Solving Vehicle Routing Problem for Intelligent Systems using Delaunay Triangulation

1st M. Sakthivel
Department of CSE
Sree Vidyanikethan Engineering College
Tirupati, India
sakthisalem@gmail.com

2nd Shashi Kant Gupta
Department of CSE
Integral University
Lucknow, India
raj2008enator@gmail.com

3rd Dimitrios A. Karras
General Department
National and Kapodistrian University of Athens (NKUA)
Psachna, Evia
dimitrios.karras@gmail.com

4th Alex Khang
Department of Information Technology
University of Science and Technology
Vietnam & USA
alexkhang.ai@gmail.com

5th Chandra Kumar Dixit
Department of Physics
Dr. Shakuntala Misra National Rehabilitation University
Lucknow, India
ckparadise@gmail.com

6th Bhadrappa Haralayya
Department of MBA
Lingaraj Appa Engineering College Bidar
Bidar, India
bhadrappabhavimani@gmail.com

***Abstract*—Intelligent Systems are of many types. This work focuses mainly about the autonomous drones and UAVs. Only for military objectives were Unmanned Aerial Vehicles (UAV) invented and developed. They have lately increased in use, nevertheless, in the civil applications this study shall examine. This technology has a wide range of applications, including in agriculture, environmental protection, public safety, and traffic flow management. The use of unmanned aerial vehicles (UAVs) in smart cities is another promising new use for this technology. By 2050, the world's population is expected to have doubled. As a result, towns and communities face new difficulties and possibilities as a result of these expectations. For any smart city design, efficiency and cost-effectiveness are the primary objectives. After the global economic downturn, people's curiosity for smart cities has grown exponentially. Unmanned aerial vehicles' (UAVs') to discover the optimal route between a source and a destination, vehicle routing is a crucial field for study. There are a number of crucial considerations to be made in order to address these challenges in vehicle routing for UAVs. UAVs must be able to see where they are in relation to the map or graph in order to make these judgments. Planned routes for unmanned aerial vehicles are not only designed to minimize the risk of collisions, but they are also designed to be as efficient as possible. To get at the end destination in the least amount of time feasible, solution for vehicle routing problems is essential. In this work, we provide a solution to the vehicle routing issue in the form of an algorithm. The use of Delaunay triangulation is done to achieve the shortest path for the intelligent systems from source to destination. The experimental findings demonstrate that the Lin-Kernighan technique performs better than alternative algorithms for addressing the vehicle routing issue.**

Keywords—Intelligent Systems, Vehicle Routing Problem, Borukuva, Delaunay Triangulation, Lin-Kernighan, Nearest Neighbor.

I. INTRODUCTION

Unmanned aerial vehicles and drones have become commonplace in the media these days, and a commercially viable, smaller version may be purchased at a discount from most electronics stores or even a neighborhood mall [1]. Considering the low cost and ease of use, these systems are presently deemed ideal for a wide range of prospective applications, even if the users lack aeronautics system expertise. For civilian use, the most common uses of unmanned aerial vehicles (UAVs) seem to include the following: In the fields of civil and military surveillance [2], 3D modeling for the reconstruction of 3D shapes of buildings or areas [3], photogrammetric and remote sensing [4], data extraction from images and the production of 3D data, and inspection [5], especially when human interventions can be dangerous, are just a few examples. Others include disaster response and monitoring [6], mapping the situation after a catastrophic event or anticipating one in advance and providing new updated information [7]. The applications of these intelligent systems are depicted in Fig.1.

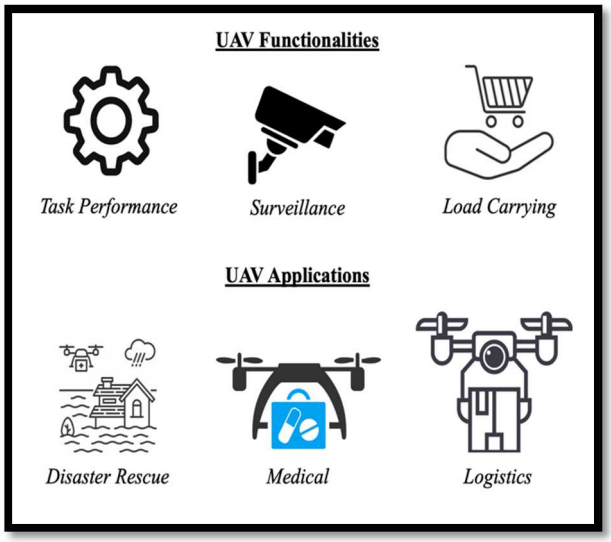

Fig. 1. UAVs applications

There are a variety of growing industries where unmanned aerial vehicles (UAVs) can offer high-resolution and repeating data essential for monitoring that make use of thermal and multispectral sensors, such as forests, agriculture, and geology [8]. UAVs may now fly autonomously following a predetermined mission plan but it is important to realize that some elements of the mission planner may not operate correctly. The pilot must take control of the UAV and land it in a safe manner in the event of an emergency. Path design for UAVs as city management tools is a major challenge, as high-rise structures and communication towers provide significant obstacle [9]. To perform tasks like distant sensing, communication, and processing on a UAV requires a precise travel plan. Finding the best path or route for a UAV to follow to reach its objective is the main goal of path planning [10]. In

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order to launch and fly from one place to another without incurring the risk of colliding with anything in their path, UAVs need route planning. Route planning for unmanned aerial vehicles (UAVs) is still difficult despite technological advancements like big data and cloud computing. This issue is even worse in smart cities since UAVs are unable to make decisions in real-time about route planning, job allocation, task scheduling, and vehicle routing. The level of autonomy granted to the UAVs is directly correlated with their crucial for UAV operations route planning processes. The traditional vehicle routing problem is depicted in Fig. 2. In this paper we have solved the problem of vehicle routing with the help of Delaunay triangulation. The related works, proposed methodology and the experimental results obtained are discussed in the subsequent sections.

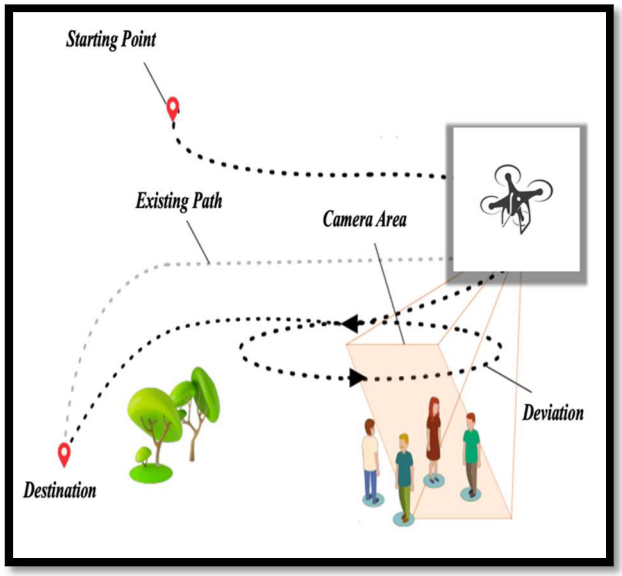

Fig. 2. Vehicle routing of UAVs

II. Related Works

In the recent years, researchers are reviewed the advancement of UAVs in [11]. There has been a fast increase in the usage of flying platforms like unmanned aerial vehicles (UAVs). Aerial base stations and transportable terminals may be set up using UAVs. UAV-based wireless communication systems may benefit from the advice in this lesson. UAV are stabilized using a unique technique suggested in this study. For example, the suggested method may be used to generate orthomosaic maps, vegetation maps, and image registrations, among other things an affine and projective transformation-based strategy to eliminating geometric distortions in video frames has been presented in [12]. When it comes to [13], service, and delivery, the drone business is a great example. For example, unmanned aerial vehicles can fly for longer periods of time, carry more cargo, and reach disaster zones more quickly. However, despite these potential qualities, such as broad use, great mobility and cost-efficiency, drones are still hindered by battery longevity, flying autonomy and confined flight duration.

Ultra-high-throughput communication and other advanced functions are expected to be facilitated by the use of THz bands in the future was discussed in [14]. There are many potential uses for THz-powered UAVs, but there are also special design limitations and trade-offs. THz band deployment regulations, standards, and health issues are discussed. When it comes to system design parameters and environmental elements, we use the case study of UAV communication as an example. It's a good thing and a bad thing that Internet-connected gadgets are becoming more and more commonplace in our everyday lives. Forensics, security, and privacy are all intertwined issues for IoT devices in this chapter's overview of the research. A conceptual model and UAV case study are used to further explore the interconnectedness of these issues was viewed in [15]. It's becoming more difficult for unmanned aerial vehicles (UAVs) to map out their flight trajectories, particularly in densely populated interior spaces. The computational complexity, sluggish convergence time, and poor flight routes of current UAV indoor trajectory planning systems severely restrict their usefulness. In order to address the difficulties outlined above, a grid-optimized UAV route planning method is developed and written in [16] and [17].

UAVs and quick coverage trajectory planning (CPP), this research [18] examines the issues and potential solutions. The onboard sensor footprint is used to build a back-and-forth route using the developed algorithm. First responders, such as police officers and firemen, may readily employ this strategy since it is integrated with appropriate software. POWELL-BINPAT provides the most efficient routes to finish the full task in the shortest amount of time possible, according to the findings. A CPP algorithm's purpose is to reduce the total covered trajectory and execution time. CPP algorithms seek to reduce overlap in the area of interest. There has been a lot of robotics research in the areas of cooperative multi-unmanned aerial vehicles (UAVs) and energy efficiency in CPP issues [19].

An explicit surface reconstruction is required when the point cloud has to be shown accurately on the surface. We provide a technique for robustly reconstructing a surface from scratch, starting with a basic surface mesh. Our technique generates high-quality surface meshes from imperfect inputs with complete automation. Author’s technique [20] was thoroughly tested using both computer-simulated and real-world scans. An O(n) incremental method has been developed for the Delaunay triangulation (DT) and the 2D Voronoi diagram (VD). A unique face-based data structure is created that uses less memory than earlier edge-based structures. VD and DT matrices are separated in [21] and [22], however the suggested data structure connects the two and allows extraction of neighborhood and geometric information from the VD. Combinatorial in nature [23], the Travelling Salesperson Problem (TSP) arises in a broad variety of industrial settings. It is possible for humans to develop near-optimal solutions in Euclidean space when given in this way. Participants, on the other hand, find it difficult to compare and choose the best alternative from a selection of pre-defined possibilities. Classification models were able to identify the best option 97 percent of the time, whereas human participants were only able to accurately choose 47 percent of the time. However, in [24], these algorithms remain intractable and expensive for networks with more than a few hundred nodes. When trained on trivially small sizes, contemporary learning-driven TSP approaches perform similarly to classical solvers, but they are unable to generalise the learned strategy to larger instances of real scales. For the first time, we've conducted a rigorous analysis of the validity of such zero-shot generalization. As author researched in [25], TSP is the underlying problem for practically all delivery-type concerns discussed here. Although the TSP is simple to grasp, it also

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poses a significant computing obstacle that must be conquered. TSP solution generation may be improved with the use of many methods, such as Nearest Neighbor and 2-option. Data-driven processes need to create place for AI-driven frameworks [26]. The goal of technological advancement is to lessen the quantity of network traffic that has to be managed and the amount of data that needs to be sent [27].

III. METHODS

The problem of this proposed work is to solve the vehicle routing problem in intelligent systems focusing mainly on UAVs. The overall workflow of the proposed model is depicted in Fig. 3. Given a geographical area where the drone or UAV needs to be deployed, we need to initially compute the vertices. These vertices are nothing but the places that the intelligent system needs to visit. The vertices are initially taken as points and is depicted in Fig. 4.

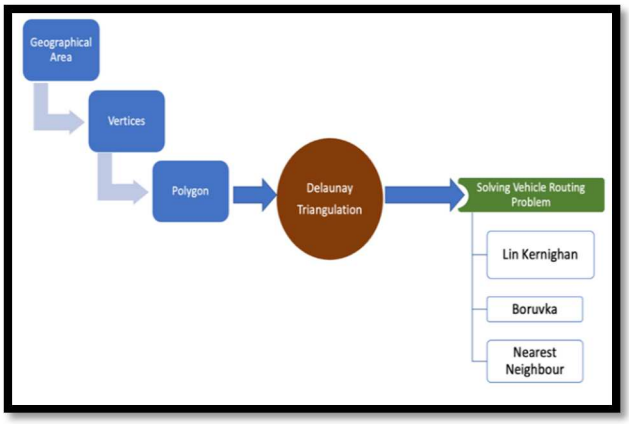

Fig. 3. Overall Workflow

Once we connect all the vertices together, we obtain the area through which the intelligent system needs to travel. The geographical area is most of the time a polygonal area as shown in Fig. 5. Once we obtain this area, we apply out proposed methodology of applying Delaunay Triangulation. The nerve of the cells in a Voronoi diagram has an identical analogue in the Delaunay triangulation, or the triangulating of the convex hull of the points in the diagram. Every point in the figure is a point within a circle under this form, and the circumcircle of every triangle is an empty circle. Once the obtained area is partitioned it looks as shown in Fig. 6.

Fig. 4. Vertices Representation

Fig. 5. Overall Workflow

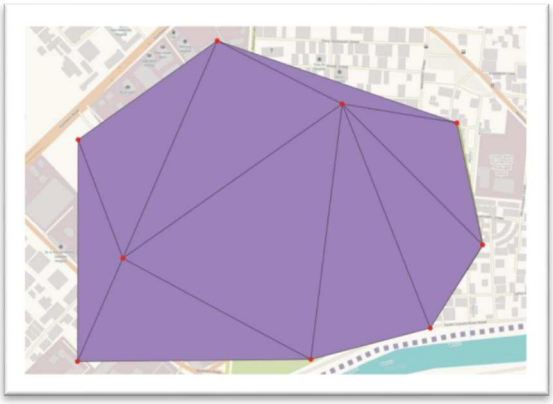

Fig. 6. Delaunay Triangulation

Once the triangulation is done to the area, we now compute the centorids of each partition. These centroids would act as the points through which the drone or UAV needs to fly autonomously. After the computation of the centroids the geographic area looks as depicted in Fig. 7.

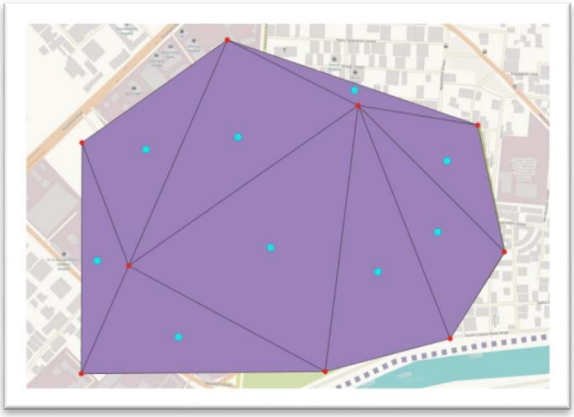

Fig. 7. Computation of Centroids

IV. RESULTS AND DISCUSSION

The proposed work of solving the vehicle routing problem for the intelligent systems was performed using the QGIS 3.10.0 with GRASS 7.8.0. This section lists out the results we obtained while performing the implementation of the proposed method. Initially the coordinates of the vertices was computed and Table 1 lists the coordinates of the vertices or the geographic area considered. Once the partitions were done, the centroids were computed or each partition and Table II shows the coordinates of the computed centroids.

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TABLE I. VERTICES COORDINATES

id	xcoord	ycoord
1	80.25828	13.07026
2	80.26058	13.07184
3	80.26265	13.07083
4	80.26454	13.07053
5	80.26497	13.06857
6	80.2641	13.06723
7	80.26213	13.06672
8	80.25826	13.06669
9	80.25902	13.06835

TABLE II. CENTROIDS COORDINATES

POINT A	xcoord	ycoord
0	80.25929	13.07015
1	80.26075	13.07034
1	80.26259	13.07107
2	80.26296	13.06826
2	80.26391	13.06888
2	80.26405	13.06998
7	80.25852	13.06843
8	80.2598	13.06725
8	80.26126	13.06864

The issue may now be framed as a Vehicle Routing Problem as the centroids are determined. The objective of the problem is to find a solution that traverses all the points and finds a shortest distance at the end. To solve this problem, we have considered using three approaches and compared them to see which algorithm works better for the proposed partitioned algorithm. The three algorithms considered for solving this problem is Borukuva, Nearest neighbor and Lin Kernighan algorithm. The routes obtained while making use of these three algorithms are shown in the Figs. 8, 9 and 10. The comparison between thee three algorithms are tabulated in Table 3. It is clear from the comparison that Lin-Kernighan algorithm outperforms the competition for our suggested partitioned method.

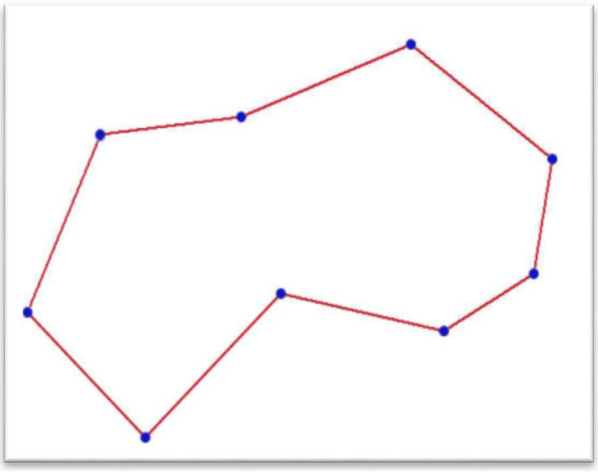

Fig. 8. Route - Lin-Kernighan

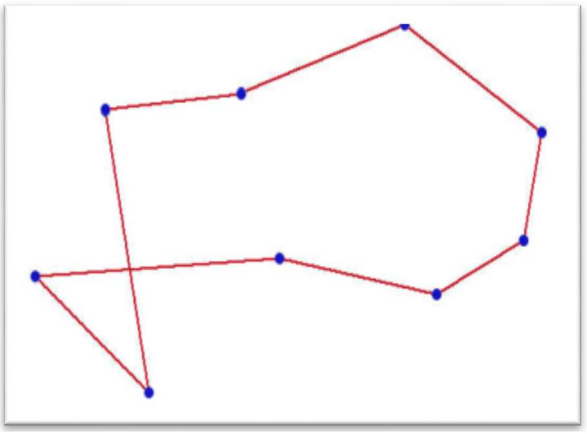

Fig. 9. Route - Borukuva

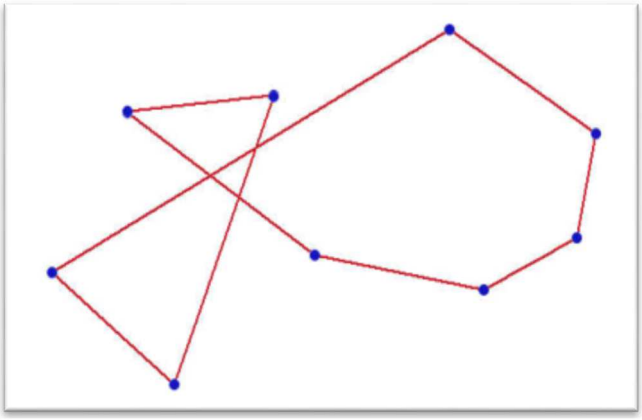

Fig. 10. Route - Nearest Neighbor

TABLE III. COMPARISON OF VARIOUS ALGORITHMS

Routing Method	Lin-Kernighan	Borukuva	Nearest Neighbor
Edges	11	11	11
Combined Length	13638001	15019875	18373658

V. CONCLUSIONS

Unmanned aircraft may execute autonomous search and localization in a cooperative environment utilizing trajectory planning, as shown in flight tests. This study is distinctive in that the cooperative control technique directly incorporates the sensing effect, which is embodied by the entire sensor model. Through a series of calculations and planning processes that are involved in route planning, the UAV may be able to overcome physical and kinetic restrictions in its courses. Three core ideas and stages of planning—navigation, trajectory, and motion planning—are linked and necessary for efficient route planning. The execution of a wide range of missions is made possible by the use of a changeable planning horizon. A broad control framework has been created by framing the problem of path planning as one of trajectory optimization. It is our belief that by employing the proposed framework of making use of the Delaunay triangulation method, as an objective function, this structure may be used to solve a variety of sensing issues, including multiple-moving target tracking. A change in application would just call for new filtering techniques and objective functions; the fundamental framework would mostly remain the same. The experimental results also show that the use of Lin-Kernighan has given the best results for the proposed algorithm.

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